Oslo Stock Exchange and the Weather

Bernt Arne Ødegaard*

October 2016

Abstract

We investigate empirical links between the Oslo Stock Exchange (OSE) and the weather, asking whether daily returns on the market, or market trading activity, seems to be related to the weather. We find a positive correlation between the OSE and two measures of "bad weather": clouds and windchill. High windchill is also associated with low market liquidity.

Everybody talks about the weather but nobody does anything about it.
(Mark Twain)

In this paper we link the stock market and the weather. There are some obvious ways in which the weather can directly influence the stock market. One is when the weather influences the running of the stock exchange, which we saw an example of after Hurricane Sandy in October 2012, where the New York Stock Exchange was closed for a record two days due to the flooding and power outtages in Manhattan.

If we instead talk about prices of stocks on the market, the weather can certainly influence stock prices through the cash flows of the firms on it. The same Hurricane Sandy resulted in large future losses to insurance companies, some of which are listed on the NYSE. So the weather can also influence the stock market that way.

In this paper we are not concerned with these *direct* influences from weather to the stock market, rather we refer to behavioral finance, where there is a long tradition for investigating a different link between the stock market and the weather, asking whether the weather influences the "mood" of participants on the exchange. If people trading on the exchange is facing a sunny spring day with wonderful weather, they may be more optimistic about the market than on one of those bleak, rainy fall days. The question we want to ask is whether we see a link between the weather faced by those people most likely to influence the stock prices in the market, which are those that live in the same city as the stock market is situated.

This was the argument in the first academic study of weather and the stock exchange, Saunders (1993), who found a negative correlation between weather in New York and returns on the exchange. The argument is that with "good" weather when they go to work, traders are more optimistic, and their trading behaviour results in higher prices when the weather is good than when it is bad. This is a recipe for an empirical investigation: Construct a measure of weather "quality," and ask whether we see an empirical link between this measure of weather quality and measures of stock prices, such as stock returns.

We will in this paper look at some such empirical examples from the Oslo Stock Exchange. We construct measures of weather quality, and ask whether the weather being better or worse than usual is correlated with measures of stock market performance.

The structure of the paper is as follows. We first, in section 1 give some references to the behavioral finance literature. Section 2 presents the data we use. Section 3 investigates the link between weather and stock returns. After a discussion, section 5 concludes.

*University of Stavanger (UiS) and Norwegian School of Economics (NHH). This paper started as a set of exercises in a PhD class in empirical finance at NHH. The paper is a (somewhat expanded) solution to the same course exercises. My sympathy to generations of students suffering through the exercises. Reflecting this pedagogical purpose, an appendix lists computer code, and on my homepage you will find data and computer code that allows any reader to replicate the results in the paper.

1 Literature

The idea is given in the before-mentioned paper by Saunders (1993), which is the starting point of the literature. Saunders makes the point that weather in New York should in general not affect the cash flows of firms on the exchange. The firms on the NYSE are claims on the cash flows of geographically diversified firms, few of which are directly exposed to New York weather. Stock returns on the NYSE should in a rational market therefore not be systematically related to New York weather. If over a very long time period (Saunder use the period 1927–1989) one observe a relationship between the observed weather in New York and the returns on the exchange, there is something wrong with the rational market hypothesis.

The argument made by Saunders is that what New York weather affects is the *mood* of traders on the stock exchange. The traders on the exchange are much more optimistic on a bright, sunny day than on a overcast or rainy day. This optimism translates into an higher view about the prospects for stock prices. Traders are more willing to buy on those optimistic days, driving prices up above the rational price. The result is a positive relationship between "good weather" and stock returns. But note that the psychological argument given by Saunders is an auxiliary hypothesis.

If we take as a starting point a hypothesed relationship between stock returns and weather, the empirical researcher's sequence of actions should be to first ask

- Is the effect there?

This is a statistical question, where we need to investigate different ways of measuring weather, stock returns, and establish beyond reasonable doubt that this effect is there, and is not an artifact of the sample, or a result of data mining.

Having established that the effect seems to be there, we need to investigate alternative explanations.

- What can cause a correlation between weather variables and stock returns?

This is where we need to consider possible alternatives to the hypothesis proposed by Saunders (1993). He states his conclusion as follows

- "Rejection of the null hypothesis supports the view that security markets are systematically influenced by investor psychology"

But as empirical researchers we should know that we rejection of the null of "no correlation between weather and stock returns" can not lead to acceptance of an alternative hypothesis unless the alternative covers all possible alternatives to the null. In this case we are not there. The psychological explanation is *one* possible explanation consistent with a correlation between stock returns and the weather, but we need to consider alternative explanations.

Possible explanations we should investigate

- Psychological biases.
- The weather variable is related to some other variable with a (rational) causal effect on stock prices.
- Weather *may* directly affect the stock market, we just don't understand the causal effect.

Once we bring in the other alternative here it is obvious that rejection of the null does not immediately lead to acceptance of the alternative of psychological biases, we need to at least make these alternative relationships less likely explanations before we end up accepting that the evidence points towards psychological biases.

The article by Saunders have spurred on other researchers to investigate the same relationships. The literature linking stock markets and meteorological observations is surprisingly extensive, but in this paper we will not give an extensive review, just give some highlights.[1]

An early effort was Hirshleifer and Shumway (2003), which extends Saunders analysis to a large number of stock markets around the world (including Oslo), and find that the correlation between market returns and sunshine is a world-wide phenomena. Extending the sample, here from New York to

[1] For a recent update on this literature, with a large number of references, see Lu and Chu (2012), and Novy-Marx (2014).

the Stock Markets of the World, is the typical way of answering the "Is the effect there?" question. So the evidence is building up that there is a correlation between weather and stock returns.

Researchers have a harder time zeroing in on how any psychological mechanism plausibly work. For example, Goetzmann and Zhu (2005), looking at portfolio decisions of individual investors, find no effect from weather to these individual decisions. They instead point to the behaviour of market makers, the professionals "keeping the wheels of Wall Street turning."

One comment on the research on the weather and the stock market is that this combines two of the most popular conversational gambits in the world. "Dreadful weather." "How is the market doing?" This type of research will therefore have a separate entertainment value for many people. Another reason for why meteorological variable are popular is the "because it is there" argument. Meteorological data sets are very extensive, and also have long time series.

2 Data

In the present paper we will use data for the Oslo Stock Exchange in Norway. We use various measures of "bad weather" and ask if they are related to changes in the return on the OSE.

2.1 Meteorological Data

Weather data is provided by the Norwegian Meteorological Service, through their web service (`eKlima.met.no`). The meteorological data available is extensive. We use data on precipitation,sunshine, cloud coverage and temperature. Table 1 gives details about daily observations available from the meteorological services.

Table 1 Weather Observations - Definitions

Weather	Code	Description
Clouds	NN	Cloud cover Total cloud cover, code 0 - 8 (0 = sky clear, 1-8 = octas of sky covered.)
Precipitation	RR_12	Precipitation (12 hours) – Amount of precipitation last 12 hours (mm)
Sunshine	OT_24	Sunshine last 24 hours – Number of hours with sunshine last 24 hours
Temperature	TA	Air temperature – Air temperature at time of observation (Degrees C)
Wind	FF	Wind Speed –in m/s measured 10 meters above ground

Source: `eklima.met.no`

If we are interested in the "mood" of traders at the Oslo Stock Exchange, we want to look at data relevant for the weather observed by local traders in Oslo. We therefore use weather observations from Blindern, the headquarters of the Norwegian Met office, which is situated at the University of Oslo, a few kilometers from the Oslo Stock Exchange. We use stock market and meteorological data starting in 1980.

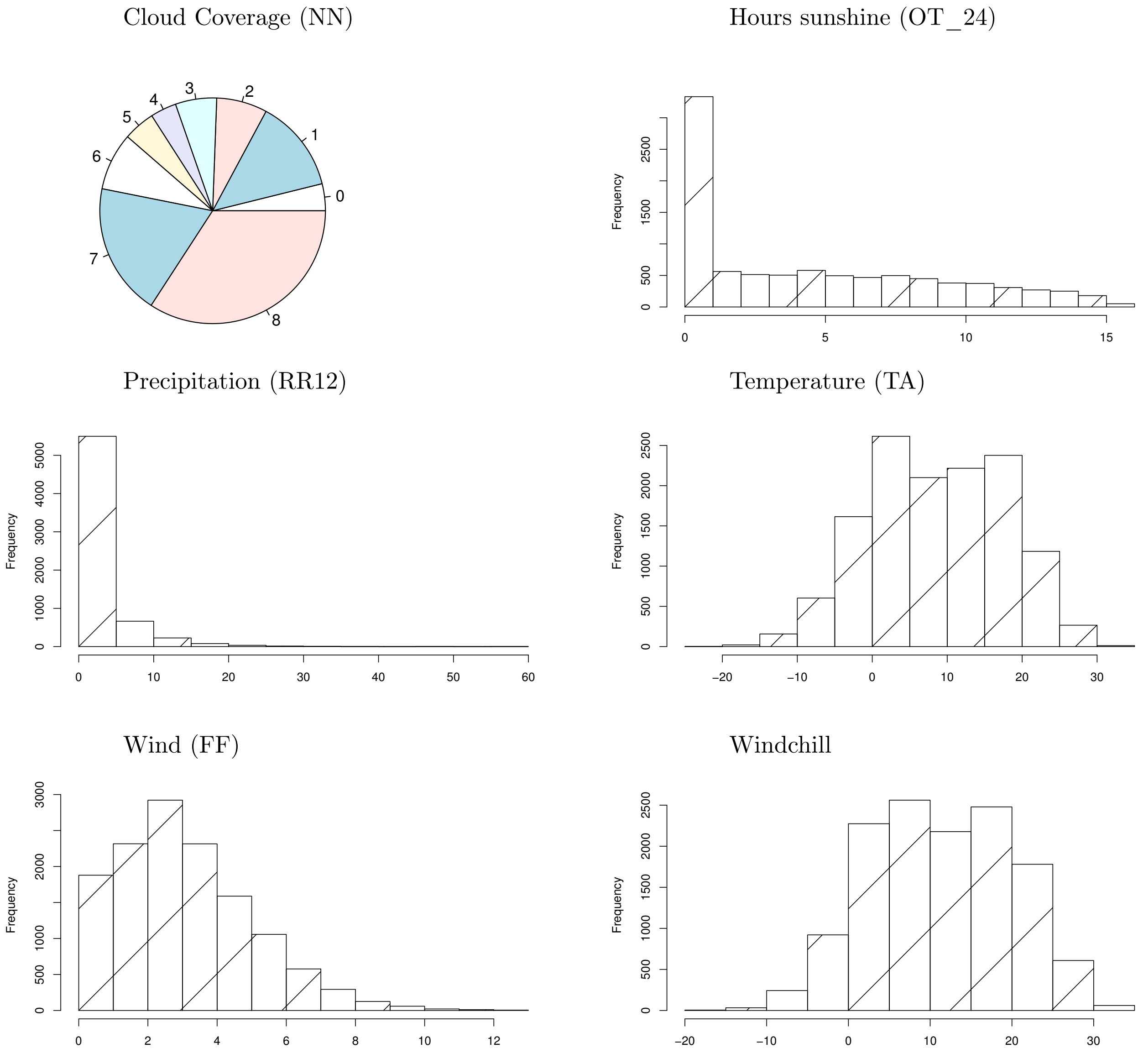
Table 2 and Figure 1 give some descriptive statistics for the meteorological data. Note that observations of Sunshine (OT_24) stops in 2005, apparently the Met Office stopped recording this variable. We also calculate a modified temperature variable which accounts for both temperature and wind, by constructing an estimate of windchill.[2]

[2] We use the windchill formula of Environment Canada:

$$T_{\mathrm{wc}} = 13.12 + 0.6215 T_{\mathrm{a}} - 11.37 V^{+0.16} + 0.3965 T_{\mathrm{a}} V^{+0.16}$$

where T_{wc} is the wind chill index, based on the Celsius temperature scale, T_{a} is the air temperature in degrees Celsius, and V is the wind speed at 10 metres (standard anemometer height), in kilometres per hour (km/h).

Figure 1 Describing the various meteorological observations



Descriptive statistics for weather observations: RR_12: Precipitation last 12 hours, NN: Cloud cover (octals – 0-sky clear), OT_24: Sunshine, Number of hours with sunshine last 24 hours. TA: Air Temperature (Decrees C). FF: Wind. Windchill. Observations are once a day. NN, OT_24: 0700, TA: 1300 and RR_12: 1900. Data 1980–2014.

Table 2 Descriptive Statistics, Weather Observations

Panel A: Descriptive statistics for each time series

	Temperature	Clouds	Sunshine	Rain	Wind
Period Start	1980	1980	1980	1980	1980
Period End	2016	2016	2005	2016	2016
Min	-20.90	0.00	0.00	0.00	0.00
Mean	8.77	5.39	4.52	2.38	3.09
Median	8.60	7.00	3.40	0.50	2.80
Max	32.40	8.00	16.00	58.90	13.00

Panel B: Correlation Matrix

	Temperature	Clouds	Sunshine	Rain	Wind
Temperature	1	-0.009	-0.205	0.498	0.123
Clouds	-0.009	1	0.193	0.080	0.045
Sunshine	-0.205	0.193	1	-0.081	0.049
Rain	0.498	0.080	-0.081	1	0.149
Wind	0.123	0.045	0.049	0.149	1

Descriptive statistics for weather observations: TA Air Temperature (Degrees C), OT_24 Sunshine, Number of hours with sunshine last 24 hours, RR_12, Precipitation last 12 hours, NN Cloud cover (octals – 0-sky clear). FF Wind Observations are once a day. TA: 1300, NN, OT_24, FF: 0700, and RR_12: 1900.

2.2 Proxies for "mood"

We want to create proxies that can be said to measure whether the weather conditions on a given day can be thought of as particularly bad (or good). Not all of the four weather variables can be used directly. Two of them, hours sunshine and air temperature, have a strong seasonal component. For example, five hours of sunshine in a day is pretty good in December, when that is most of the hours when the sun is above the horizon, but is not all that good in June, when the sun can stay above the horizon for sixteen hours. The same is true for temperature. We therefore correct for season the following ways: For sunshine we construct a proxy for "lots of sunshine" by calculating the fraction of the day with sunshine, dividing the number of hours of sunshine (OT_24) by the length of the day. For temperature we construct a "mood" variable by subtracting the observed temperature by the "normal temperature" that day. We normalize the windchill by subtracting the windchill of the "normal temperature" assuming a wind of zero.

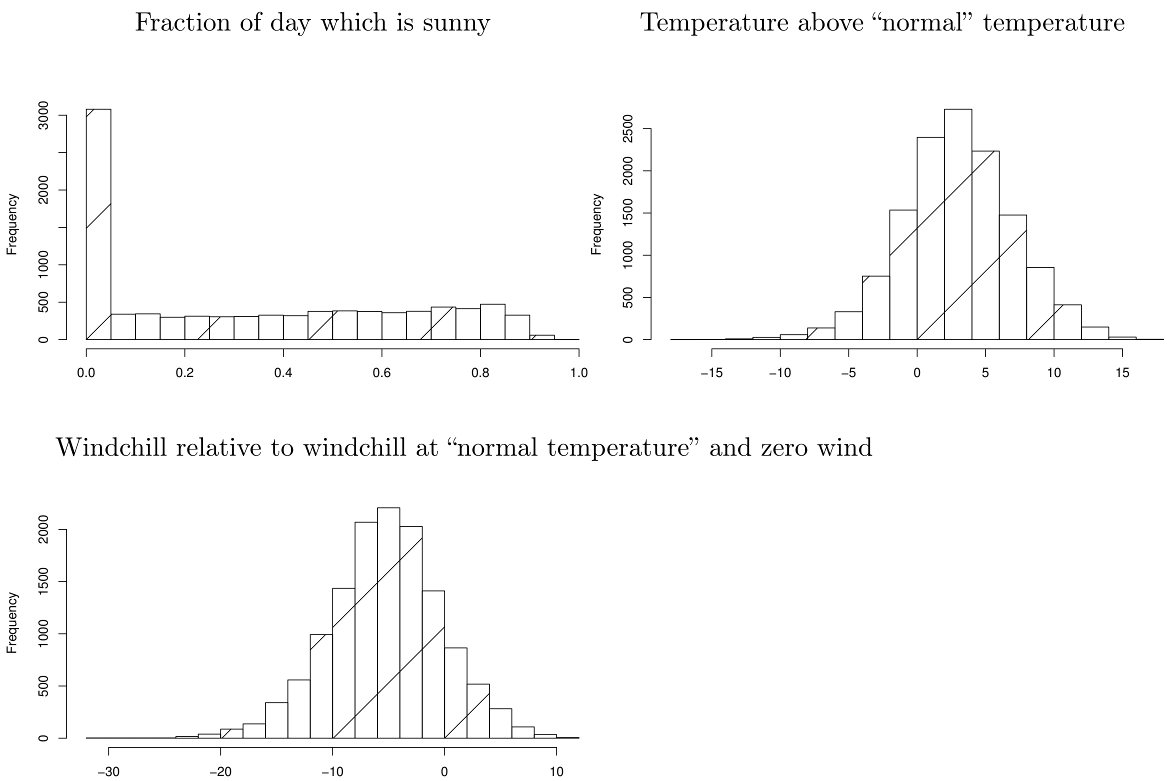
Figure 2 illustrates the distributions of these three variables. Looking at the fraction of days with sun, one observes that Oslo is not California, most days the citizens of Oslo does not see the sun once. On the other hand, if we believe the psychological hypothesis, days *with* sunshine should give a *very* good mood.

2.3 Stock market variables

To proxy for the stock market we use an equally-weighted index of stocks on the OSE.[3] Figure 3 shows the evolution of the market index in the period.

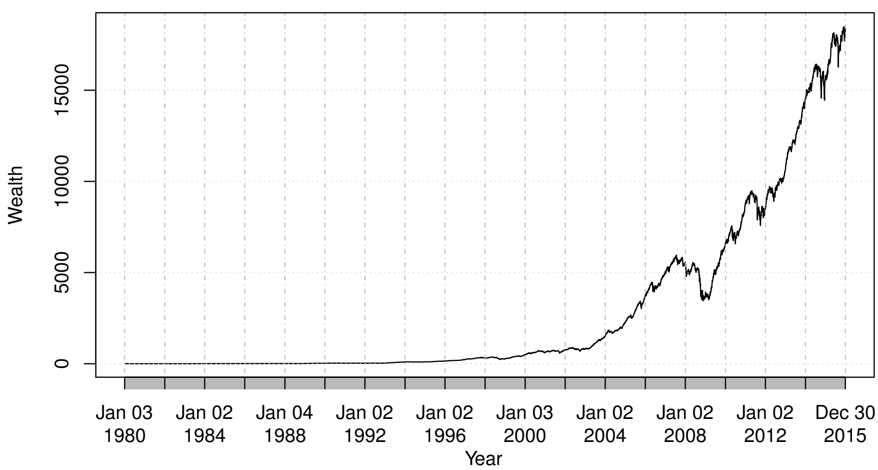
[3]We have also done estimations using the Oslo Stock Exchange all-share index, the market-wide index calculated by the Oslo Stock Exchange. The index is constructed by splicing the current AllShare index with the earlier TOTX index. The results using this index is available on request.

Figure 2 Constructed metereological "mood" variables



Distributions of constructed “mood” meteorological variables. The fraction of day which is sunny is calculated by diving the number of hours of sunshine (OT_24) with the length of the day. (Calculated using the R module `geosphere`.) Temperature above normal temperature is calculated by subtracting the temperature observation (TA) by the normal temperature also downloaded from `eKlima`

Figure 3 Stock Market Index



Evolution of stock market value, constructed by aggregating the EW returns on the OSE.

3 Linking weather and returns

To investigate the link between weather and stock returns we estimate the following regression

$$R_{m,t} = a + bW_t + \varepsilon_t \qquad (1)$$

where R_m is the daily return on the stock market, and W_t the value of the weather variable. We consider one market index, `EW`, and five weather variables measuring Temperature, Rain, Sunshine, Cloud coverage, and Windchill.

Table 3 Estimating links between OSE market returns and weather variables

	Dependent variable:				
	R_m^{EW}				
Temperature	−0.00001				
	(0.00002)				
Rain		−0.00004			
		(0.00003)			
Sunshine			0.0003		
			(0.0004)		
Cloud Coverage				-0.0001^{***}	
				(0.00004)	
WindChill					-0.0001^{***}
					(0.00002)
Constant	0.001^{***}	0.001^{***}	0.001^{***}	0.002^{***}	0.001^{***}
	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0001)
Observations	9,024	4,479	6,325	8,713	9,024
Adjusted R^2	−0.0001	0.0002	−0.0001	0.001	0.001
Note:				*p<0.1; **p<0.05; ***p<0.01	

Results for different regressions $R_{m,t} = a + bW_t + \varepsilon_t$ where R_{mt} is the return on the stock market (in percent), and W_t is a weather variable. The five weather variables are: Temperature: The difference between observed temperature and a "normal" temperature. Rain: Precipitation in mm. Sunshine: Fraction of day with sunshine. Cloud coverage: NN. Windchill: Difference between calculated Windchill and Windchill of normal temperature with zero wind.

The estimation results are shown in table 3. There is two weather variable that significantly predicts the stock market, cloud coverage and wind chill. First, the more clouds, the lower the return on the Oslo Stock Exchange. This is the same result as Saunders (1993) found for New York. The significant relationship between windchill and the stock market is new to the literature.

However, even if the variables are statistically significant, note the $\bar{R}^2$ of all these regressions. They are all very close to zero.

4 Discussion

We have found a significant relationship between two measures (of five possible) of the quality of weather *that day* and movement of the aggregate stock market. What should we conclude from that? Saunders (1993) presents this as a choice between two alternative hypotheses.

1. Efficient markets – if markets are efficient, New York (or Oslo) weather should not affect the prices of companies at the NYSE.

2. Behavioral explanations – The weather affects the *mood* of market participants, which again affect their view of where the market is going.

With this perspective, if we find a correlation between weather and stock returns, we would reject efficient markets and accept the alternative behavioral explanation

However, there is a number of issues with this simplified statement of the problem.

1. The usual *statistical* question: While we do find two significant coefficients, can we really say that the effect is there?
2. Can we really say that efficient markets rule out New York weather having effects on prices of companies listed at the NYSE?
   - Could there be direct cash flow effects?
   - Could weather and stock returns be connected through some unobserved third variable/relationship?
3. One should have the behavioral explanation fleshed out and identified before we can accept a *causal* behavioral relationship.
4. While there may be a statistical relationship, is it an *economically significant* relationship?

4.1 Is the effect a statistical artifact?

One can of course never answer this question completely, but there are some ways of gauging it. A common method is to do a *Placebo* regression, replacing the explanatory variable with some alternative variable *less* connected with one of the explanations, and see whether we get significance. So how about weather in a couple of alternative geographical locations, where the weather is sufficiently different from Oslo. We gather data for Lindesnes, at the south tip of Norway, and Bergen, on the west coast. In terms of behavioral explanations, weather elsewhere should be less likely to affect *mood* in Oslo.

Table 4 Descriptive Statistics, Weather Observations for Placebo Locations

Panel A: Bergen

	Temperature	Clouds	Sunshine	Rain	Wind
Period Start	1980	1980	1980	1982	1980
Period End	2015	2015	2005	2015	2015
Min	-12.70	0.00	0.00	0.00	0.00
Mean	9.87	5.77	3.14	4.86	3.45
Median	9.50	7.00	0.90	2.00	3.10
Max	31.10	8.00	16.40	76.70	22.60

Panel B: Lindesnes

	Temperature	Clouds	Rain	Wind
Period Start	1980	1980	1980	1980
Period End	2015	2015	2015	2015
Min	-17.60	0.00	0.00	0.00
Mean	7.71	5.26	3.31	7.74
Median	7.70	6.00	1.40	6.70
Max	24.50	8.00	84.00	30.90

Descriptive statistics for four weather observations: TA Air Temperature (Degrees C), OT_24 Sunshine, Number of hours with sunshine last 24 hours, RR_12, Precipitation last 12 hours, NN Cloud cover (octals – 0-sky clear). FF Wind Observations are once a day. TA: 1300, NN, OT_24, FF: 0700, and RR_12: 1900.

Let us first give some descriptives for the weather variables, shown in table 4. We note that Bergen, for example, has significantly more rain than Oslo. We use these weather observations to construct the same "mood" variables as was done for Oslo, and use them in regressions with the return of the OSE as the dependent variable. Table 5 shows results for the "placebo regressions." Here we see that we get less cases of significance, closer to what one could get by chance. The significant explanatory variable in Bergen is temperature, which is different from any of the variables in Oslo. For Lindesnes we get Windchill, the same variable as in Oslo.

Table 5 Placebo Regressions

Panel A: Bergen

	Dependent variable:				
	R_m^{EW}				
Temperature	-0.0001^{**}				
	(0.00003)				
Rain		-0.00002			
		(0.00002)			
Sunshine			-0.0001		
			(0.0004)		
Cloud Coverage				-0.00003	
				(0.00004)	
WindChill					-0.0001
					(0.00004)
Constant	0.001^{***}	0.001^{***}	0.001^{***}	0.001^{***}	0.001^{***}
	(0.0001)	(0.0002)	(0.0001)	(0.0002)	(0.0003)
Observations	9,020	5,587	6,396	8,944	4,023
Adjusted R^2	0.001	0.0002	-0.0001	-0.00004	0.0003
Note:					*p<0.1; **p<0.05; ***p<0.01

Panel B: Lindesnes

	Dependent variable:			
	R_m^{EW}			
Temperature	-0.00002			
	(0.00003)			
Rain		-0.00004		
		(0.00003)		
Cloud Coverage			-0.00004	
			(0.00004)	
WindChill				-0.0001^{***}
				(0.00003)
Constant	0.001^{***}	0.001^{***}	0.001^{***}	0.0002
	(0.0001)	(0.0002)	(0.0002)	(0.0002)
Observations	8,994	4,494	8,766	8,954
Adjusted R^2	-0.0001	0.0002	0.0001	0.002
Note:				*p<0.1; **p<0.05; ***p<0.01

Results for different regressions $R_{m,t} = a + bW_t + \varepsilon_t$ where R_{mt} is the return on the stock market, and W_t is a weather variable, observed in Bergen. The four weather variables are: Temperature: The difference between observed temperature and a "normal" temperature. Rain: Precipitation in mm. Sunshine: Fraction of day with sunshine. Cloud coverage: NN. (octals – 0-sky clear).

4.2 Behavioral explanations?

If we want to argue for a behavioral explanation, ideally need some more specifics about how this explanation is supposed to work in terms of how it affects trading on the exchange. The value of the stock market index is the sum of prices of individual stocks. Stock prices change as a result of many trading decisions by individual traders. If we want to argue for a behavioral explanation, some of these *traders* must change their behavior, in a way that pushes prices in a direction influenced by the weather.

If we think about traders on a stock exchange, one useful categorization in this context is

- Professional `traders`. These are market professionals, which on average have zero net positions. One type of such a trader is a "market maker."
- "The buy side." These are institutional / individual investors with a portfolio view of their asset holdings.

How are these traders likely to be affected by "mood"? If it affects professional traders, we may see effects on traded quantity, or trading behavior, which show up in the liquidity of the trading process on the exchange. For the "Buy Side" traders we should see changes in portfolio composition as a result of weather changes.

Let us take the case of professional traders. As said, if they change their trading behavior, it can affect

- market liquidity
- traded quantity in the market

Let us look at whether weather affects such variables. To investigate this we, instead of returns, use measures of stock market *liquidity* as dependent variables:

$$Liq_{m,t} = a + bW_t + \varepsilon_t \tag{2}$$

where L_m is a measure of stock market liquidity, and W_t the value of the weather variable. We consider two liquidity measures, `Relative Spread` and `Turnover`, and the same five weather "mood" variables.

The estimation results are shown in table 6. We find one variable that also is consistently related to liquidity, namely windchill. The worse the windchill, the less turnover, and the higher relative spread, i.e. liquidity is worse on cold, windy days. That may not be that surprising, cold, windy days in Oslo are more likely to be days when transportation breaks down (snowstorms), and people just stay home. So Windchill is actually a weather variable that may affect trading (and liquidity) at the OSE. But it is not clear why it should push returns down. Maybe the pessimists stay at home, and the optimists are so exhausted getting to work that they turn pessimists...

We do not find the same link between liquidity and cloud coverage as we find for returns, but both rain and temperature is linked to one measure of liquidity each.

If we wanted to look at buy side traders, we would need to investigate actual portfolio decisions. This is not feasible with the data we use here, but e.g. Goetzmann and Zhu (2005), looking at individual traders, find no effect on portfolio compositions of weather.

Table 6 Estimating links between OSE market activity and weather variables

Panel A: Turnover

	Dependent variable:				
	Turnover				
	(1)	(2)	(3)	(4)	(5)
Temperature	0.00003***				
	(0.00000)				
Rain		−0.00001			
		(0.00001)			
Sunshine			−0.0001		
			(0.0001)		
Cloud Coverage				0.00001	
				(0.00001)	
WindChill					−0.00002***
					(0.00000)
Constant	0.003***	0.003***	0.003***	0.003***	0.003***
	(0.00002)	(0.00003)	(0.00004)	(0.00004)	(0.00003)
Observations	9,022	4,479	6,322	8,711	9,022
Adjusted R^2	0.003	0.00004	−0.00004	0.0001	0.002
Note:					*p<0.1; **p<0.05; ***p<0.01

Panel B: Relative Spread

	Dependent variable:				
	RelSpread				
	(1)	(2)	(3)	(4)	(5)
Temperature	−0.00004				
	(0.00003)				
Rain		0.0001***			
		(0.00004)			
Sunshine			−0.0004		
			(0.0004)		
Cloud Coverage				−0.00003	
				(0.00004)	
WindChill					0.00005**
					(0.00002)
Constant	0.034***	0.032***	0.036***	0.034***	0.034***
	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0001)
Observations	9,022	4,479	6,322	8,711	9,022
Adjusted R^2	0.0002	0.003	0.00003	−0.00002	0.0004
Note:					*p<0.1; **p<0.05; ***p<0.01

Results for different regressions $Liq_{m,t} = a + bW_t + \varepsilon_t$ where Liq_{mt} is a measure of stock market liquidity, and W_t is a weather variable. The four weather variables are: Temperature: The difference between observed temperature and a "normal" temperature. Rain: Precipitation in mm. Sunshine: Fraction of day with sunshine. Cloud coverage: NN.

4.3 Left out variables?

We did find that some weather variables are significantly related to stock market variables. As mentioned, any empirical researcher should always be looking for alternative explanations for any observed empirical regularity. One possibility is that what we find is due to weather being related to some *other* variable affecting stock returns. One possibility is a well known effect in finance, seasonality, that there seems to be a regular variation in stock returns related to calendar month, which is illustrated in table 7, showing average returns by month for four different equity indices at OSE.

Table 7 Monthly effects

Month	EW	VW	TOT	OBX
Jan	5.6	4.0	3.3	1.9
Feb	3.0	2.1	1.8	2.2
Mar	2.3	1.9	2.2	2.4
Apr	3.2	4.3	3.5	2.7
May	1.5	2.2	1.5	1.1
Jun	-0.6	-0.2	-0.7	-0.4
Jul	2.6	3.1	2.2	2.3
Aug	0.0	0.6	-0.6	-1.2
Sep	-1.1	-0.7	-1.6	-2.3
Oct	0.8	1.7	0.4	0.2
Nov	0.4	0.2	-0.6	-0.6
Dec	2.1	3.2	2.8	2.8

The table shows percentage monthly returns split by month for four different stock market indices at the OSE. Source Ødegaard (2016),

Let us illustrate how one can check if such effects may be behind the significant coefficients on the weather variables. We use the July effect of Hong and Yu (2009), that stock prices in July reflect the fact that many of the regular participants in the market is on holiday, which may affect the efficiency of pricing. Tables 8 show the result of adding a dummy for July to the regressions explainging returns. Adding the holiday dummy does not make us change our previous conclusions, it actually strengthens them.

Table 8 Estimating links between OSE market returns and weather variables

	Dependent variable:				
	R_m^{EW}				
Temperature	-0.00001				
	(0.00002)				
Rain		-0.00004			
		(0.00003)			
Sunshine			-0.0005		
			(0.0004)		
Cloud Coverage				-0.0001^{***}	
				(0.00004)	
WindChill					-0.0001^{***}
					(0.00002)
July	0.0004	0.0003	0.001	0.0004	0.001^{**}
	(0.0003)	(0.0005)	(0.0004)	(0.0003)	(0.0004)
Constant	0.001^{***}	0.001^{***}	0.001^{***}	0.002^{***}	0.001^{***}
	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Observations	9,024	4,479	6,324	8,713	9,024
Adjusted R^2	-0.00004	0.0001	0.0002	0.001	0.001
Note:			*p<0.1; **p<0.05; ***p<0.01		

Results for different regressions $R_{m,t} = a + bW_t + \varepsilon_t$ where R_{mt} is the return on the stock market, and W_t is a weather variable. The five weather variables are: Temperature: The difference between observed temperature and a "normal" temperature. Rain: Precipitation in mm. Sunshine: Fraction of day with sunshine. Cloud coverage: NN. WindChill. In addition we include a dummy variable for July.

5 Conclusion

We investigate links between daily stock returns at the Oslo Stock Exchange and Oslo Weather. We find that cloudy days and cold, windy days are associated with lower returns.

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A Appendix: R code

This paper started as a set of exercises in a PhD class in empirical finance at NHH. The paper is a (somewhat expanded) solution to the same course exercises. Reflecting this pedagogical purpose, the appendix lists complete computer code used to do the analysis. The code and data is also available on my homepage. The analysis is done using the `R` statistical computing environment.

A.1 Reading the data

The structure of the data is illustrated by the first five lines of the input file:

```
...
St.no;Year;Mnth;Date;Time(NMT);TA;OT_1;OT_24;RR_24;RR_12;WW;NN
18700;1980;1;1;7;-3.2; ;3.3; ;0.3;2;8
18700;1980;1;1;13;-3.1; ; ; ; ;2;6
18700;1980;1;1;19;-4.5; ; ; ;-1;1;2
18700;1980;1;2;7;-6.4; ;4.6; ;-1;2;1
18700;1980;1;2;13;-5.2; ; ; ; ;2;1
18700;1980;1;2;19;-6.8; ; ; ;-1;2;0
...
```

R code for reading this file:

```r
#reading the blindern data
library(xts)

datadir <- "/home/bernt/data/2016/eklima/2016_jan/"
filename <- paste0(datadir,"blindern_1980_2014.csv")
obs1 <- read.table(filename, skip=32,sep=";",header=TRUE,na.strings="x")
head(obs1)
tail(obs1)
filename <- paste0(datadir,"blindern2015.csv")
obs2 <- read.table(filename, skip=25,sep=";",header=TRUE,na.strings="x")
head(obs2)
tail(obs2)

dates1 <- as.POSIXct(paste(obs1$Year,obs1$Mnth,obs1$Date,obs1$Time,sep="-"),format="%Y-%m-%d-%H")
dates2 <- as.POSIXct(paste(obs2$Year,obs2$Mnth,obs2$Date,obs2$Time,sep="-"),format="%Y-%m-%d-%H")

TempBlindern1 <- na.omit(xts(obs1$TA, order.by=dates1))
TempBlindern2 <- na.omit(xts(obs2$TA, order.by=dates2))
TempBlindern <- rbind(TempBlindern1,TempBlindern2);
names(TempBlindern) <- "TA"

OT24Blindern1 <- na.omit(xts(obs1$OT_24,order.by=dates1))
OT24Blindern2 <- na.omit(xts(obs2$OT_24,order.by=dates2))
OT24Blindern <- rbind(OT24Blindern1,OT24Blindern2)
names(OT24Blindern) <- "OT24"

RR12Blindern1 <- na.omit(xts(obs1$RR_12,order.by=dates1))
RR12Blindern2 <- na.omit(xts(obs2$RR_12,order.by=dates2))
RR12Blindern <- rbind(RR12Blindern1,RR12Blindern2)
RR12Blindern <- RR12Blindern[RR12Blindern>=0]
names(RR12Blindern) <- "RR12"

NNBlindern1 <- xts(obs1$NN, order.by=dates1)
NNBlindern2 <- xts(obs2$NN, order.by=dates2)
NNBlindern <- rbind(NNBlindern1,NNBlindern2)
NNBlindern <- na.omit(NNBlindern)
NNBlindern <- NNBlindern[NNBlindern>=0]
names(NNBlindern) <- "NN"

WWBlindern1 <- na.omit(xts(obs1$WW, order.by=dates1))
WWBlindern2 <- na.omit(xts(obs2$WW, order.by=dates2))
WWBlindern <- rbind(WWBlindern1,WWBlindern2)
WWBlindern <- WWBlindern[WWBlindern>=0]
names(WWBlindern) <- "WW"
```

```
FFBlindern1 <- na.omit(xts(obs1$FF, order.by=dates1))
FFBlindern2 <- na.omit(xts(obs2$FF, order.by=dates2))
FFBlindern <- rbind(FFBlindern1,FFBlindern2)
FFBlindern <- FFBlindern[FFBlindern>=0]
names(FFBlindern) <- "FF"
                                        # daily normals is one observation for each date
                                        # in a "normal year" Create a time series by adding years
norm <- read.table("../../data/met_data_blindern/blindern_air_temperature_daily_normals.txt",
                   skip=11,sep=";",header=TRUE)
ntemps <- NULL
ndates <- NULL
for (y in 1980:2015){
  ndates <- c(ndates,as.Date(paste(y,norm$Mnth,norm$Date,sep="-"),format="%Y-%m-%d"))
  ntemps <- c(ntemps,as.matrix(norm$X18700))
}
normtempsBlindern <- xts(ntemps,order.by=as.Date(ndates))
names(normtempsBlindern) <- "NormTemp"
```

R code for transforming the data into what is necessary for analysis

```
#library(lubridate)
library(geosphere)

                                    # for the temperature pick the observations at midday, 13:00
                                    # because the normal temperature is at midday
TempBlindern <- TempBlindern[as.character(index(TempBlindern),"%H")=="13"]
                                    # wind at the same time as temperature
FFBlindern <- FFBlindern[as.character(index(FFBlindern),"%H")=="13"]
                                    # pick the rainfall observed at the end of the day
RR12Blindern <- RR12Blindern[as.character(index(RR12Blindern),"%H")=="19"]
                                   # pick the cloud coverage observed in the morning
NNBlindern <- NNBlindern[as.character(index(NNBlindern),"%H")=="07"]

                                    # now convert the posix dates to regular date classes, so can do econometrics
OT24Blindern <- xts(as.matrix(OT24Blindern),as.Date(index(OT24Blindern)))
names (OT24Blindern) <- "OT24"
RR12Blindern <- xts(as.matrix(RR12Blindern),as.Date(index(RR12Blindern)))
names (RR12Blindern) <- "RR12"
NNBlindern <- xts(as.matrix(NNBlindern), as.Date(index(NNBlindern)))
names(NNBlindern) <- "NN"
FFBlindern <- xts(as.matrix(FFBlindern), as.Date(index(FFBlindern)))
names(FFBlindern) <- "FF"
TempBlindern <- xts(as.matrix(TempBlindern),as.Date(index(TempBlindern)))
names(TempBlindern) <- "TA"
data <- merge(TempBlindern,normtempsBlindern)
DiffMeanTemp <- data$TA - data$NormTemp
names(DiffMeanTemp) <- "DiffMean"
                                    # the OT stuff needs to be converted a bit
                                    # first we lag by one day, since the observation is at 7 in the morning
                                    # the following day
OT24Blindern <- lag(OT24Blindern,-1)
                                    # then we construct the variable that measures
                                    # the fraction of the day with sunshine
length <- daylength(59,as.Date(index(OT24Blindern))) # Blindern is at 59 north
FracDaySunny <- OT24Blindern/length
names(FracDaySunny) <- "FracDaySunny"

data <- merge(TempBlindern,FFBlindern,normtempsBlindern,all=FALSE)
temp <- data$TA
wind <- data$FF * (1000/3600)
normtemp <- data$NormTemp
                                    #convert from m/s to km/h
windchill <- 13.12 + 0.6215 * temp -11.37 *wind^0.16 + 0.3965 * temp * wind^0.16
                                    # calculate an windchill adjusted normal temperature
                                    # assuming wind equal average of wind
#meanwind <- mean(wind)
meanwind <- 0
windchill_normal <- 13.12 + 0.6215 * normtemp - 11.37 * (meanwind)^0.16 + 0.3965 * normtemp * (meanwind)^0.16

DiffWindChill <- windchill - windchill_normal
names(DiffWindChill) <- c("DiffWindChill")
head(DiffWindChill)
```

A.2 Producing figures describing the data

```
# for the temperature pick the observations at midday, 13:00

filename <- paste0(outdir,"blindern_temperature_time_series.eps")
postscript(filename,horizontal=FALSE,height=5,width=10)
plot(TempBlindern)
dev.off()

filename <- paste0(outdir,"blindern_temperature_histogram.eps")
postscript(filename,horizontal=FALSE,height=5,width=10)
hist(as.matrix(TempBlindern),main="",density=TRUE,xlab="")
dev.off()

filename <- paste0(outdir,"blindern_OT24_time_series.eps")
postscript(filename,horizontal=FALSE,height=5,width=10)
plot(OT24Blindern, main ="OT24,Blindern")
dev.off()

filename <- paste0(outdir,"blindern_OT24_histogram.eps")
postscript(filename,horizontal=FALSE,height=5,width=10)
hist(as.matrix(OT24Blindern),main="",density=TRUE,xlab="")
dev.off()

filename <- paste0(outdir,"blindern_RR12_time_series.eps")
postscript(filename,horizontal=FALSE,height=5,width=10)
plot(RR12Blindern,main="RR12,Blindern",xlab="")
dev.off()

filename <- paste0(outdir,"blindern_RR12_histogram.eps")
postscript(filename,horizontal=FALSE,height=5,width=10)
hist(as.matrix(RR12Blindern),main="",density=TRUE,xlab="")
dev.off()

filename <- paste0(outdir,"blindern_normtemp_time_series.eps")
postscript(filename,horizontal=FALSE,height=5,width=10)
plot(normtempsBlindern,main="normtemp,Blindern",xlab="",)
dev.off()

filename <- paste0(outdir,"blindern_normtemp_histogram.eps")
postscript(filename,horizontal=FALSE,height=5,width=10)
hist(as.matrix(normtempsBlindern),main="normtemp, Blindern",density=TRUE,xlab="")
dev.off()

filename <- paste0(outdir,"blindern_NN_time_series.eps")
postscript(filename,horizontal=FALSE,height=5,width=10)
plot(NNBlindern,main="NN,Blindern",xlab="")
dev.off()

cnt <- table(NNBlindern)
filename <- paste0(outdir,"blindern_NN_pie_chart.eps")
postscript(filename,horizontal=FALSE,height=5,width=10)
pie(cnt)
dev.off()

filename <- paste0(outdir,"blindern_NN_histogram.eps")
postscript(filename,horizontal=FALSE,height=5,width=10)
hist(as.matrix(NNBlindern),main="NN, Blindern",density=TRUE,xlab="")
dev.off()

filename <- paste0(outdir,"blindern_WW_time_series.eps")
postscript(filename,horizontal=FALSE,height=5,width=10)
plot(WWBlindern,main="WW,Blindern",xlab="")
dev.off()

cnt <- table(WWBlindern)
filename <- paste0(outdir,"blindern_WW_pie_chart.eps")
postscript(filename,horizontal=FALSE,height=5,width=10)
pie(cnt)
dev.off()
```

```
filename <- paste0(outdir,"blindern_WW_histogram.eps")
postscript(filename,horizontal=FALSE,height=5,width=10)
hist(as.matrix(WWBlindern),main="WW, Blindern",density=TRUE,xlab="")
dev.off()

filename <- paste0(outdir,"blindern_diff_temp_normtemp_histogram.eps")
postscript(filename,horizontal=FALSE,height=5,width=10)
hist(as.matrix(DiffMeanTemp),main="",density=TRUE,xlab="")
dev.off()

filename <- paste0(outdir,"blindern_diff_temp_normtemp_time_series.eps")
postscript(filename,horizontal=FALSE,height=5,width=10)
plot(DiffMeanTemp,main="Difference mean and normtemp, Blindern",xlab="")
dev.off()

filename = paste0(outdir,"blindern_FracDaySunny_time_series.eps")
postscript(filename,horizontal=FALSE,height=5,width=10)
plot(FracDaySunny, main ="Fraction of Day with sun,Blindern")
dev.off()

filename = paste0(outdir,"blindern_FracDaySunny_histogram.eps")
postscript(filename,,horizontal=FALSE,height=5,width=10)
hist(as.matrix(FracDaySunny),main="",density=TRUE,xlab="")
dev.off()

filename = paste0(outdir,"blindern_wind_histogram.eps")
postscript(filename,,horizontal=FALSE,height=5,width=10)
hist(as.matrix(FFBlindern),main="",density=TRUE,xlab="")
dev.off()

filename = paste0(outdir,"blindern_windchill_histogram.eps")
postscript(filename,,horizontal=FALSE,height=5,width=10)
hist(as.matrix(windchill),main="",density=TRUE,xlab="")
dev.off()

filename = paste0(outdir,"blindern_windchill_minus_normal_histogram.eps")
postscript(filename,,horizontal=FALSE,height=5,width=10)
hist(as.matrix(DiffWindChill),main="",density=TRUE,xlab="")
dev.off()
```

A.3 Regression predicting returns

```
                                      # now do regressions
                                      # temperature is observed the same day,
                                      # so can use the return on the same day in regression

data <- merge(ew,DiffMeanTemp,all=FALSE)
print(head(data))
retew <- as.matrix(data$ew)
names(retew)[1]="ew"
diffmean <- as.matrix(data$DiffMean)
regr1 <- lm(retew ~ diffmean)

                                      # use rainfall to predict.
                                      # rain observed at the evening, so can use the same date
names(RR12Blindern)[1] <- "RR12Blindern"
print(head(RR12Blindern))
data <- merge(ew,RR12Blindern,all=FALSE)
head(data)
rain <- as.matrix(data$RR12Blindern)
names(rain)[1] <- "Rainfall"
retew <- as.matrix(data$ew)
names(retew)[1] <- "ew"
regr2 <- lm(retew ~ rain)
                                      # fraction of day with sun
data <- merge(ew,FracDaySunny,all=FALSE)
head(data)
FracSunny <- as.matrix(data$FracDaySunny)
names(FracSunny)[1] <- "FractionSunny"
retew <- as.matrix(data$ew)
names(retew)[1] <- "ew"
regr3 <- lm(retew ~ FracSunny)

                                      #  use cloud cover, on the same date
data <- merge(ew,NNBlindern,all=FALSE)
head(data)
cloud <- as.matrix(data$NN)
names(cloud)[1] <- "Cloud"
retew <- as.matrix(data$ew)
names(retew)[1] <- "ew"
regr4 <- lm(retew ~ cloud)

                                      # windchill
data <- merge(ew,DiffWindChill,all=FALSE)
head(data)
retew <- as.matrix(data$ew)
names(retew)[1]="ew"
diffmeanwind <- as.matrix(data$DiffWindChill)
regr5 <- lm(retew ~ diffmeanwind)

tabl <- stargazer(regr1,regr2,regr3,regr4, regr5,
                  model.numbers=FALSE,
                  omit.stat=c("ser","f","rsq"),
                  float=FALSE,
                  dep.var.labels=c("$R_m^{EW}$","$R_m^{EW}$","$R_m^{EW}$","$R_m^{EW}$","$R_m^{EW}$"),
                  covariate.labels=c("Temperature","Rain","Sunshine","Cloud Coverage","WindChill","Constant"),
                  title="Explaining stock returns at the Oslo Stock Exchange with Oslo Weather")
filename <- paste0(outdir,"blindern_regr_returns_ew.tex")
cat(tabl,file=filename, sep="\n")
```

A.4 Regression predicting liquidity

```
data <- merge.xts(Turnover,RelSpread,DiffMeanTemp,all=FALSE)
head(data)
turnover <- as.matrix(data$Turnover)
names(Turnover)[1]="Turnover"
diffmean <- as.matrix(data$DiffMean)
lregr1 <- lm(turnover ~ diffmean)
relspread <- as.matrix(data$RelSpread)
names(relspread)[1]="RelSpread"
lregr2 <- lm(relspread ~ diffmean)

data <- merge(Turnover,RelSpread,RR12Blindern,all=FALSE)
head(data)
rain <- as.matrix(data$RR12Blindern)
names(rain)[1] <- "Rainfall"
turnover <- as.matrix(data$Turnover)
names(turnover)[1] <- "Turnover"
lregr3 <- lm(turnover ~ rain)
relspread <- as.matrix(data$RelSpread)
names(relspread)[1] <- "RelSpread"
lregr4 <- lm(relspread ~ rain)

data <- merge.xts(Turnover,RelSpread,FracDaySunny,all=FALSE)
head(data)
FracSunny <- as.matrix(data$FracDaySunny)
names(FracSunny)[1] <- "FractionSunny"
turnover <- as.matrix(data$Turnover)
names(turnover)[1] <- "turnover"
lregr5 <- lm(turnover ~ FracSunny)
relspread <- as.matrix(data$RelSpread)
names(relspread)[1] <- "relspread"
lregr6 <- lm(relspread ~ FracSunny)

data <- merge.xts(Turnover,RelSpread,NNBlindern,all=FALSE)
head(data)
cloud <- as.matrix(data$NN)
names(cloud)[1] <- "Cloud"
turnover <- as.matrix(data$Turnover)
names(turnover)[1] <- "Turnover"
lregr7 <- lm(turnover ~ cloud)
relspread <- as.matrix(data$RelSpread)
names(relspread)[1] <- "RelSpread"
lregr8 <- lm(relspread ~ cloud)

                                        # windchill
data <- merge(Turnover,RelSpread,DiffWindChill,all=FALSE)
head(data)
turnover <- as.matrix(data$Turnover)
names(turnover)[1] <- "Turnover"
diffmeanwind <- as.matrix(data$DiffWindChill)
regr9 <- lm(turnover ~ diffmeanwind)
relspread <- as.matrix(data$RelSpread)
names(relspread)[1] <- "RelSpread"
regr10 <- lm(relspread ~ diffmeanwind)

tabl <- stargazer(lregr1,lregr3,lregr5,lregr7,regr9,
                  omit.stat=c("ser","f","rsq"),
                  float=FALSE,
                  dep.var.labels=c("Turnover","Turnover","Turnover","Turnover","Turnover"),
                  covariate.labels=c("Temperature","Rain","Sunshine","Cloud Coverage","WindChill","Constant"),
                  title="Explaining stock liquidity at the OSE with Oslo Weather")
filename <- paste0(outdir,"blindern_regr_liquidity_turnover.tex")
cat(tabl,file=filename,sep="\n")

tabl <- stargazer(lregr2,lregr4,lregr6,lregr8,regr10,
                  omit.stat=c("ser","f","rsq"),
                  float=FALSE,
                  dep.var.labels=c("RelSpread","RelSpread","RelSpread","RelSpread"),
```

```
          covariate.labels=c("Temperature","Rain","Sunshine","Cloud Coverage","WindChill","Constant"),
          title="Explaining stock liquidity at the OSE with Oslo Weather")
filename <- paste0(outdir,"blindern_regr_liquidity_relspread.tex")
cat(tabl,file=filename,sep="\n")
```